Deep Learning model for Corona Virus Disease (COVID-19) from X-ray chest images

Abstract

The COVID-19 pandemic has strained healthcare systems worldwide, resulting in overcrowded hospitals and limited access to diagnostic testing in both developed and underdeveloped nations. Real-time polymerase chain reaction (RT-PCR) testing, while effective, is resource-intensive and not always accessible. This study presents a deep learning model for automated COVID-19 diagnosis using chest X-ray images as an alternative solution. Our proposed model employs a convolutional neural network (CNN) consisting of three incremental convolutional blocks and a fully connected multilayer perceptron (MLP). With an accuracy of 98.2%, this approach can detect pneumonia caused by COVID-19, providing a valuable tool for remote areas with limited test kit availability, individuals unable to afford testing, and healthcare providers in need of rapid testing support

Keywords: Convolutional Neural Networks, Deep Learning, COVID-19, X-Ray Image Analysis

THE DATASET AND METHODOLOG

To train our proposed model to identify COVID-19's pneumonia patterns, we used three different sources of X-ray images. The first source was a COVID-19 X-ray image database developed by Joseph Paul Cohen , which contained 310 X-ray images from patients who tested positive for COVID-19. The second source was a database of 108 X-ray images from patients diagnosed with pneumonia caused by COVID-19, collected from a local hospital in Guayaquil, the epicenter of the outbreak in Ecuador. Finally, we utilized a third collection of X-ray images identified as normal, which was a dataset available on Kaggle . This dataset consisted of 418 radiology images of confirmed COVID-19 cases and 420 images of subjects considered normal.

Also, before training, we run some pre-processing procedures on the images; such as, resizing to a size of 200×200 pixels, this reduction in size decreased the number of parameters to be learn for our model; and, rescaling based on the image's standard deviation, because the datasets came from different sources, with scale-variance imposed by image resolutions, and considering that the CNN will be capable of ignoring slight positional variance.

We have implemented three different methods and networks for the purpose of detecting the coronavirus.

First method

The architecture of the classification model, has been designed to recognize the presence, or not, of the pneumonia patterns from CONVID- 19; hence, it has been configured to solve a binary classification problem where the goal was to detect, whether or not there is enough evidence of COVID-19 infection, as detected in the X-ray image.

For training our model, we use Stochastic Gradient Descent (SGD) with momentum, a method that helps accelerate SGD in a relevant direction and inhibits oscillations. In our experiments we have set the momentum to 0.9, and the learning rate to 5x10-3. Training was performed with 134 batches of size 10, and the parameter's search was performed for 50 epochs.

Our proposed model for detecting the coronavirus is based on a Deep Convolutional Neural Network architecture that includes three convolutional blocks. This architecture is similar to the Visual Geometry Group-VGG block architecture , and we have included batch normalization to standardize the inputs.

To maximize the features in the region covered by the filter, we employ a max-pooling operation in our model. This is achieved by sliding a two-dimensional filter with a size of 2x2 over each channel of the feature maps that are created after the convolutional blocks. The max-pooling method we used to downsize the input is based on the maximum of a region determined by the 2x2 filter in every pooling operation.

THE PROPOSED MODEL and RESULTS

Our deep convolutional neural network-based model achieved an impressive accuracy of 98.4% for the binary classification task of COVID-19 and non-COVID-19, defined as normal. The model comprises three incremental convolutional blocks that are used to extract image features, and a fully connected MLP as the classifier. To ensure the model's robustness, it was evaluated using 17-fold cross-validation procedures, repeating the experiments 17 times.

During the 50 epochs of training, the model registered the training and validation accuracy for each epoch,in our project code.

According to loss during the training, there is a significant increase in the loss values at the beginning of the training process, which decreases considerably after about eight epochs of training. This is due to the deep learning model analyzing each X-ray image during the training process, and the loss improves significantly as the model explores the images repeatedly.

Second method

Our second approach utilizes a network architecture similar to previous model.

Our proposed model for detecting coronavirus is based on a deep convolutional neural network architecture that consists of two convolutional blocks. The architecture includes a Conv2D layer with 32 filters of size 3x3, followed by a MaxPooling2D layer with a 2x2 filter, and a Dropout layer with a rate of 0.5. The second convolutional block includes a Conv2D layer with 64 filters of size 3x3, followed by a MaxPooling2D layer with a 2x2 filter, and another Dropout layer with a rate of 0.5. The output of the second convolutional block is flattened and connected to a dense layer with 256 units, followed by another Dropout layer with a rate of 0.5, and finally a dense layer with a single output unit. The model contains a total of 41,014,209 parameters, all of which are trainable. During training, the Adam optimizer is used with a learning rate of 0.001 for 50 epochs

THE PROPOSED MODEL and RESULTS

During the training process of 50 epochs, our proposed model was evaluated on both training and validation datasets. The evolution of the accuracy values for each epoch is in our project code.

According to loss value , we observed an initial increase in the loss values, which decreased considerably after the first eight epochs of training. This behavior can be attributed to the deep learning model analyzing each X-ray image during the training process. As the model repeatedly explores the images, it gradually learns to distinguish between normal and infected cases, leading to a significant improvement in the loss values.

The proposed method achieved an accuracy of 89%, which is significantly less than the accuracy obtained by our first network.

Third method

This method includes three main steps which are divided into two phases.

A. Pre-processing (Yellow block)

To prepare the dataset for the training phase of our deep learning model, we performed two key pre-processing steps:

1. Data augmentation A deep learning model requires a large dataset for the training phase. For this purpose, data augmentation operation has been done by using a part of train data. To perform it, rotation method is used on each sample.

2. Data normalization Normalization operation in image processing is a common primary phase as data preprocessing that changes the range of pixel intensity values. Its main purpose is to convert an input image into a range of pixel values with more familiar senses. To perform data normalization each input image is divided into 255 values as the maximum intensity

B. First DNN model (Blue block)

The first learning model applies a deep neural network to separate normal class from COVID-19 and pneumonia classes. An inception module has been incorporated into the deep model architecture to improve feature extraction. Inception module approximates an optimal local sparse structure model. In other words, inception module allows to use multiple types of filter size in a single image block rather than being restricted to a single filter size. Figure 1 depicts InceptionV3 module that used in our model.

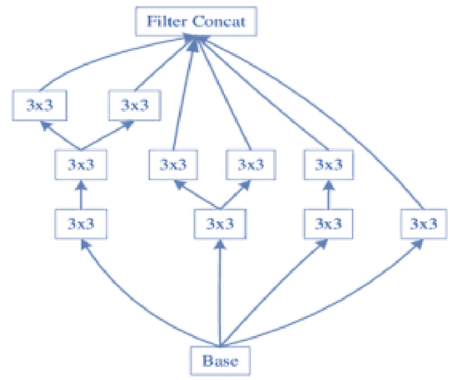

Figure 1: InceptionV3 module architecture

C. Second DNN model (Green block)

If the result of the first DNN model corresponding to input image is not normal, then the type of the disease must be diagnosed. In the second model, an architecture similar to the first model is used to determine the type of disease.

RESULTS

Parametric results of the proposed method are train, validation and test accuracy and train, validation and test loss. For accuracy and loss sparse_categorical_accuracy and sparse_categorical_crossentropy are applied, respectively.Accuracy and the loss indicated in our code in 20 epochs.

Conclusion

The use of artificial intelligence and machine learning algorithms are of great importance today. The accuracy of the algorithms is essential for diagnosis and identification of diseases. Deep learning is highly regarded in the medical fields due to its high accuracy in disease detection. In this study, a hierarchical approach based on deep learning was used to distinguish covid-19 and pneumonia from normal images. Implementing a hierarchical approach, improved the classification of the output class. By changing a triple classes model into two double classes model and applying them hierarchically, a more accurate module has creates for separating covid19 and pneumonia classes.

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